

# MODELING TECHNIQUES AND PROCESSES CONTROL APPLICATION BASED ON NEURAL NETWORKS WITH ON-LINE ADJUSTMENT USING GENETIC ALGORITHMS

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**Abstract** - In this work a strategy is presented for the temperature control of the polymerization reaction of styrene in suspension in batch. A three-layer feed forward Artificial Neural Network was trained in an off-line way starting from a removed group of patterns of the experimental system and applied in the recurrent form (RNN) to a Predictive Controller based on a Nonlinear Model (NMPC). This controller presented very superior results to the classic controller PID in the maintenance of the temperature. Still to improve the performance of the model used by NMPC (RNN) that can present differences in relation to the system due to the dead time involved in the control actions, nonlinear characteristic of the system and variable dynamics; an on-line adjustment methodology of the parameters of the exit layer of the Network is implemented, presenting superior results and treating the difficulties satisfactorily in the temperature control. All the presented results are obtained for a real system.

**Keywords:** Predictive Control; Neural Networks; Genetic Algorithms; Polystyrene; Artificial Intelligence.

## INTRODUCTION

Styrene polymerization process in suspension for obtaining polystyrene using monofunctional initiators, such as Benzoyl Peroxide (BPO) presents difficulties in temperature control of the chemical reaction, given the nonlinear characteristics of the reaction kinetics, which is exothermic. From 30% conversion of monomer into polymer, there is an increase in the viscosity, leading to the occurrence of the gel effect, reducing the mobility of the larger molecules and increasing the reaction rate

significantly, making control of temperature more difficult.

Maintenance of operation temperature is directly linked to the final product characteristics. Variations of temperature in batch reactions can affect the degree of monomer conversion and polymer molecular weight, which in turn can lead, undesirably, to a product outside of specifications.

Many literature works have approached the problem of temperature control. In the work of Ray (1986), a discussion presents problems in the control of polymerization processes. Multivariable nonlinear

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control is a field to be developed by researchers. We can also mention lack of appropriate conditions for on-line measurement, for instance, of monomer conversion rates and the lack of understanding of the highly nonlinear dynamics of the polymerization processes which present nonlinear kinetics. These are challenges to overcome in the control of polymerization processes. Later, the work of Khalid and Omatu (1992) presented a comparison between the classic PI controller and a controller based on an Artificial Neural Network (ANN) trained in an off-line form for temperature control of a chemical process in batch, with better results for the model-based controller.

In the work of Crowley and Choi (1996), the difficulty in the temperature control of a batch suspension polymerization reaction of methyl methacrylate due to the gel effect was emphasized. Application of the classical PID controller, associated with a dead time compensation algorithm, can present a satisfactory performance (Ingimundarson and Hägglund, 2001; Shinsky, 2001). However, the variation of the dynamics and the nonlinearities can degrade the controller performance. The use of an approach that can appropriately treat the problem of the nonlinearities, together with the disturbances not modeled and the intrinsic variations in the process dynamics will certainly guarantee a safer operation.

More recently, the work of Chen and Huang (2004) presents results using Neural Networks to extract parameters that allow updating controllers PID in nonlinear processes. Unfortunately, only simulations are presented in that work. Later, Heejin et al. (2004) used an Artificial Neural Network to estimate the deactivation catalyst factor used in the process of obtaining styrene monomer, with good results according to the authors. Xiong and Zhang (2005) present an application of Neural Networks to preview properties of the polymer resulting from peroxide-initiated batch polymerization of methyl methacrylate, with satisfactory results.

This work approaches the use of Artificial Neural Networks associated with Genetic Algorithms for temperature control of the batch polymerization reaction of styrene in suspension. This process is characterized by three rather different stages: heating of the reactor up to the desired temperature for the reaction; maintenance of the operational conditions until desired conversion is reached; cooling and discharge of the reactor. Each stage has different dynamics and dead times that, together with the nonlinearities of the control valves and highly exothermic reaction demand adequate techniques (or strategies) of control.

A Predictive Controller Based on a Nonlinear

Model (NMPC) is used to fulfill the temperature control of the polymerization reactor. A three layer Artificial Neural Network of the Feedforward type (FANN) was applied in a recurrent form as the model of the process (RNN), as described by Cancelier (2004) and Marcolla (2005). Because the dynamics of the system presented significant variations, an on-line adjustment of the weights and bias in the RNN output layer was implemented using Genetic Algorithms (GA) to correct these deviations. Results obtained were compared to the PID performance for control of the same process and with NMPC controller performance without adaptation, and results were superior for the adaptive strategy.

## EXPERIMENT

### Chemical Reaction

The polymerization was carried out in a batch reactor containing 1.5 liters of styrene in 3.5 liters of water; about 4.6 g of BPO – benzoyl peroxyde (initiator) was added, the temperature was raised to 90°C and, one hour and thirty minutes from the moment that 90°C was obtained, Poly(vinylpyrrolidone) (PVP) (suspension agent) was added. Agitation was maintained at 500 rpm during the experiment. After the time of reaction necessary to reach the desired conversion, the reactor was cooled and discharged.

### Experimental Unit

The experimental unit is basically a jacketed reactor made of 316L stainless steel, with five liters capacity, equipped with a mixing system operated by software with a three phase motor, a frequency controller and a centered double turbine type agitator. Thermal swaps are performed by a cross-current plate-type heat exchanger, a hydraulic pump, two pneumatic valves for the dosage of the hot and cold currents. A termopar measures the temperature inside the reactor. A boiler supplies steam to the heating system. Tap water is used in the cooling system. Thermal change system is initiated by the centrifugal pump that causes the pressure in the jacket of the reactor to be approximately 2 kgf/cm<sup>2</sup>. Valve U<sub>1</sub> is responsible for steam circulation in the plate heat exchanger, through which the hot current is generated for heating. If valve U<sub>2</sub> is closed, only the hot current circulates in the reactor.

The opening of valve U<sub>2</sub> reduces the pressure in the reactor jacket as well as in every circulation line so that the cold water stream circulates in it. Figure 1 presents the schematic of the equipment.

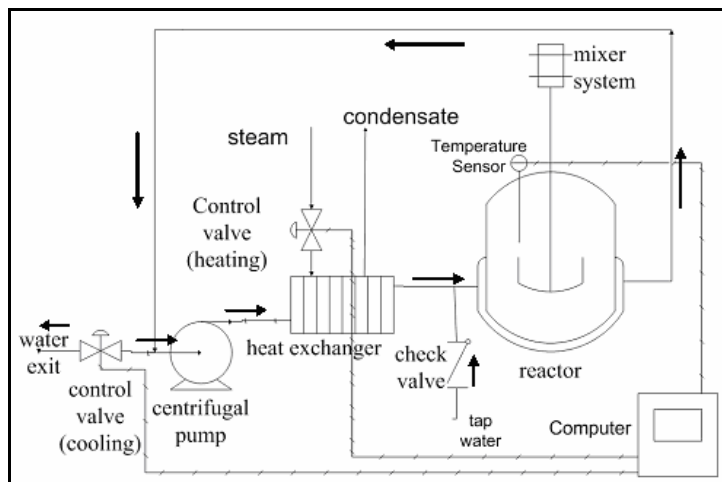


Figure 1: Pilot plant scheme used.

**System Representation**

The system under study was identified from a series of disturbances applied to the control valves, resulting in a group of patterns for a three layer Feedforward Artificial Neural Network off-line training, being five neurons in the hidden layer, which will be used in order to represent the system on a Predictive Controller.

The activation function applied to the neurons in the hidden layer is the hyperbolic tangent.

Resulting groups of patterns were re-arranged according to the identified dead time for the heating and cooling processes in a polymerization reactor, in order to have a better representation through the FANN used.

Figure 2 shows the patterns used and the disturbances applied to the system valves. Figure 10 shows the topology of the FANN used in recurrent form. Table 1 presents the building of training patterns for FANN.

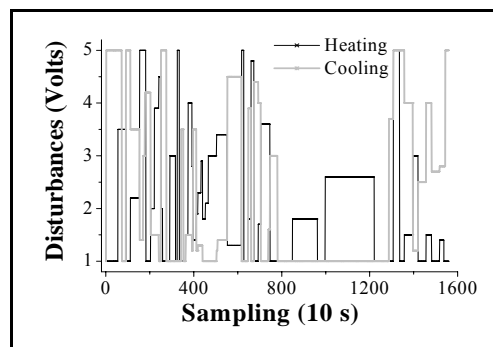
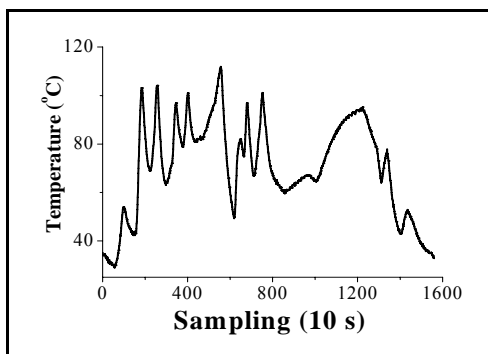


Figure 2: Patterns used for FANN training and Applied disturbances to system.

Table 1: Formation of FANN training patterns.

Instant (k)	y(k)	y (k-1)	U <sub>1</sub> (k-5)	U <sub>2</sub> (k-4)	Target y (k+1)
1	y(1)	y(1)	U <sub>1</sub> (1)	U <sub>2</sub> (1)	y(1)
2	y(2)	y(2)	U <sub>1</sub> (2)	U <sub>2</sub> (2)	y(2)
3	y(3)	y(3)	U <sub>1</sub> (3)	U <sub>2</sub> (3)	y(3)
4	y(4)	y(4)	U <sub>1</sub> (4)	U <sub>2</sub> (4)	y(4)
5	y(5)	y(5)	U <sub>1</sub> (5)	U <sub>2</sub> (5)	y(5)
6	y(6)	y(6)	U <sub>1</sub> (6)	U <sub>2</sub> (6)	y(6)
7	y(7)	y(7)	U <sub>1</sub> (7)	U <sub>2</sub> (7)	y(7)

Dead time involved in the heating and cooling processes was determined from a comparison between graphical methodology, where a disturbance to the system was applied and where response time to the disturbance, as well as minimum squares methodology from the group of patterns initially created.

Dead time used for the heating action consisted of five sampling intervals and, for cooling action, four sampling intervals, using a sampling interval of 10 seconds.

The FANN training was done using a hybrid algorithm proposed by Claumann (1999), using Genetic Algorithms to train the FANN intermediate layer and Minimum Square for the FANN output layer.

A topology to be adopted for the FANN must be that one that presents the simplest structure and, at the same time, capable of adjusting to the training data with good capacity of generalization.

### Data and Control Acquisition Software

System temperature and agitation frequency in the experimental unit were remote controlled by a PC-Intel Pentium-S 200MHz microcomputer, data acquisition board AD/DA from Data Translation model DT2812 and software for real time processing developed in the laboratory. Figure 3 shows the software main screen developed for the control strategies and data acquisition application. The software was developed in Object-Pascal language,

using the integrated environment for Borland Delphi 5.0 development.

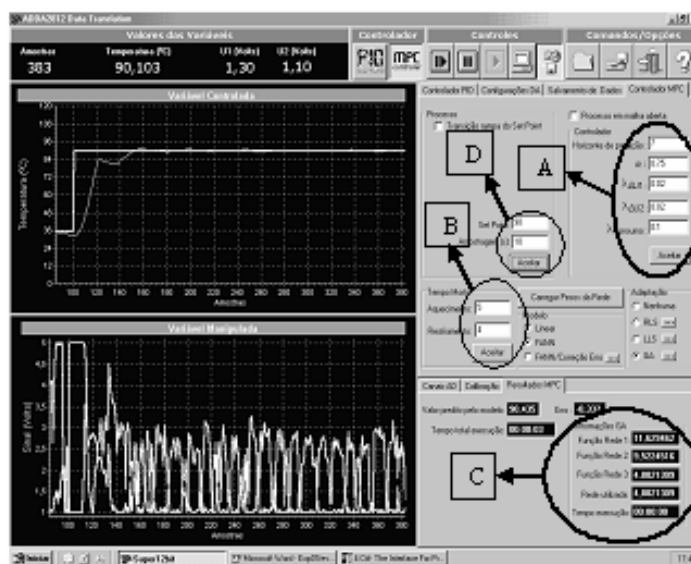
### PID Controller

The PID controller applied to fixed parameters was tested for the temperature control system being studied, for changes in the temperature, first for the polymerization reactor containing only water inside, where later it lead to a chemical reaction of the polymerization of styrene in suspension. The result for no chemical reaction was satisfactory; however, for the second case, with a leading polymerization chemical reaction, results were not satisfactory given dynamic changes in the system as well as dead times involved.

The controller was adjusted according to Cohen-Coon classical methodology, considering first order system as dead time; as shown in Equation 1, controller's parameters were better adjusted manually by trial and error. The values used were the following:  $K_c = 1.8$ ;  $T_i = 144.1$  and  $T_d = 7$ , representing controller gain, integrative and derivative constants, respectively, the identification procedure used can be found in Marcolla (2005).

$$Y(s) = \frac{Ke^{-\theta s}}{(\tau s + 1)} \quad (1)$$

where:  $\theta = 0.835$  min;  $K = 3.04$  ( $^{\circ}\text{C}$ ) / (% opening valve);  $\tau = 25.93$  min.



**Figure 3:** Control system main screen (“A” represents the adjust of parameters  $N$ ,  $\alpha$ ,  $\lambda_1$ ,  $\lambda_2$ ,  $\lambda_c$ . “B” represents the adjust of delays  $d_1$  and  $d_2$ . “C” represents value of minimization function. “D” represents the adjust of sample time and set-point).

## NMPC Controller

NMPC Controller application using the Artificial Neural Network trained in off-line form was verified, with the network applied to the system in recurrent form (RNN), for the reactor containing only water and for the leading chemical polymerization reaction. NMPC minimizes the objective function presented in Equation 2 using:  $\lambda_c = 0.1$ ,  $N = 7$ ,  $\lambda_1$  and  $\lambda_2 = 0.02$  and  $\alpha = 0.75$ . These values result after a manual adjustment until the controller shows the desired performance. Further details of the controller parameters adjustment can be seen in section 2.7. The aim when minimizing Equation 2 is that the future exit follows the reference and, at the same time, control efforts are minimized. Equation 2 has several degrees of freedom ( $N_1$ ,  $N_2$ ,  $N_u$ ,  $\lambda_1$ ,  $\lambda_2$ , and  $\lambda_c$ ) that can be modified to obtain the desired behavior of the controlled system. In Equation 2, “k” and “j” represent the current instant and other time instants and  $U_1$  and  $U_2$  are the control actions for the system.

$$J(N_1, N_2, N_u) = E \left\{ \begin{array}{l} \sum_{j=N_1}^{N_2} (y(k+j) - w(k+j))^2 + \\ \lambda_1 \sum_{j=1}^{N_u} (\Delta U_1(k+j-1))^2 + \\ \lambda_2 \sum_{j=1}^{N_u} (\Delta U_2(k+j-1))^2 + \\ \lambda_c \sum_{j=1}^{N_u} ((U_1 - 1)(k+j-1))^2 \end{array} \right. \quad (2)$$

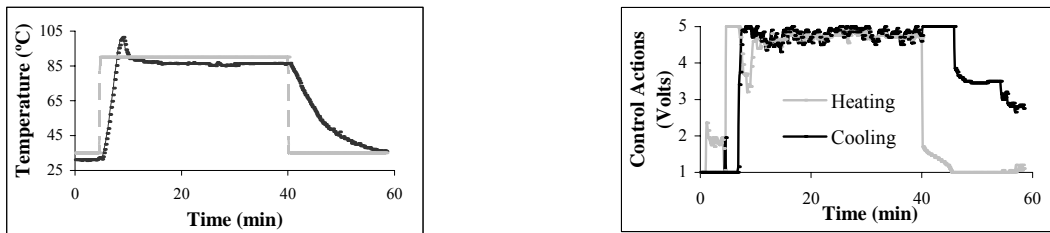
$N_1$  ( $\min(d_1, d_2) + 1$ ) and  $N_2$  ( $\max(d_1, d_2) + 1 + N$ ) vary according to delay values ( $d_1, d_2$ ) identified in the system as well as with the prediction horizon  $N$ . The value of  $N_u$  (control horizon) is kept constant and equals one, since the control problem is solved step by step. The parameter  $\lambda_c$  determines the importance of the work strip in the heating system valve  $U_1$  for the minimization of the objective function. The term  $[(U_1 - 1)(k+j-1)]$  represents the weight of the control action for the valve  $U_1$  in the objective function, and when valve  $U_1$  (heating valve) is closed, there is no influence on the rise of the objective function regarding such control action, given the restrictions

of the signal sent to the actuator. Parameter  $\alpha$  represents the coefficient of the reference path  $w(t+k)$  and it varies from 0 to 1 with application as follows:  $w(t+k) = \alpha w(t+k-1) + (1-\alpha)r(t+k)$ ; where  $k = 1 \dots N$

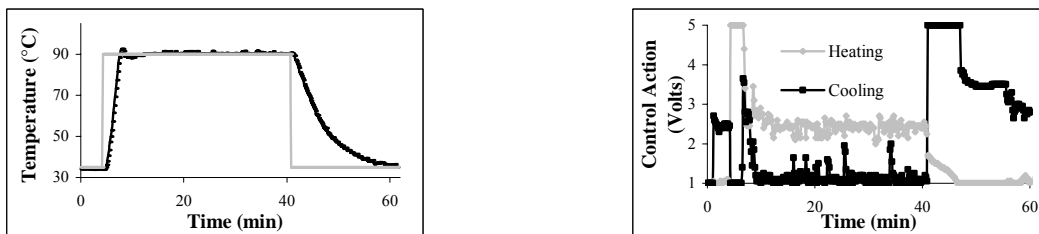
The value of the prediction horizon  $N$  must be defined as an acceptable value for its RNN prediction capacity. Parameters  $\lambda_1$  and  $\lambda_2$  represent a greater influence than can be given to the control actions in the objective function. The algorithm used to define the control actions at each instant determines the values of  $U_1$  and  $U_2$  in view of the best prediction of the system, that is, the smaller value of the objective function.

### Adjustment of the Controller Parameters: Influence on Control System Performance

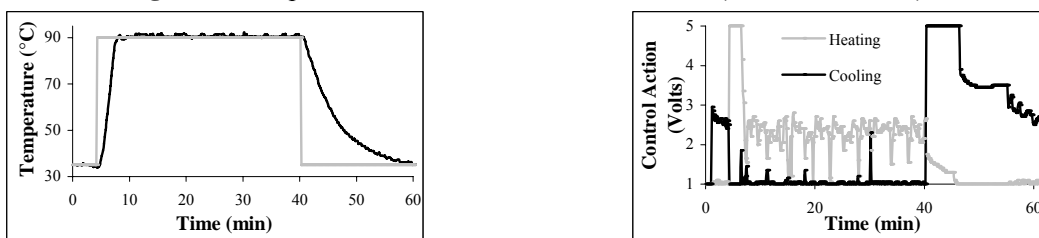
Figures 4, 5 and 6 show system behavior of  $\lambda_c$  varying from 0.001; 0.01 and 0.1; with  $\alpha = 0.75$ ; horizon prediction ( $N$ ) = 7 and  $\lambda_1 = \lambda_2 = 0.02$ . A very small value for the parameter  $\lambda_c$  harms the controller performance because the valves operate in a very high opening range. With the parameter  $\lambda_c$  value already reduced, there is smaller degree of freedom applied to the system; the restriction on the steam consumption allows for better controller performance. Parameter  $\alpha$  represents the coefficient of the reference path; this parameter varies from 0 to 1. Lower values of  $\alpha$  provide a faster transition for the reference,  $r(t+k)$ , while higher values makes the transition slower. Figures 7, 6 and 8 show the reference transition ( $\alpha$ ) for the case of  $\alpha$  values of 0.50 and 0.75 and 0.96, respectively, horizon prediction ( $N$ ) = 7 and  $\lambda_1 = \lambda_2 = 0.02$  and  $\lambda_c = 0.1$ . In this case, the overshoot could be reduced by simply modifying this parameter ( $\alpha$ ) with a higher value, turning the path slower for the reference, allowing for a softer transition. If the aim was for the system not to present overshoot, this simple adjustment could solve the problem. In case the value of  $\alpha$  is reduced, the transition is expected to be faster but the overshoot larger. The performance controller for the case of a differentiated horizon prediction can also be seen, like the case of a horizon prediction with seven sampling intervals,  $\lambda_c = 0.1$  and  $\alpha = 0.75$  (Figure 6) and the case of a horizon prediction ( $N$ ) of 12 sampling intervals,  $\lambda_c = 0.1$  and  $\alpha = 0.75$  (Figure 9). Very high values for this parameter ( $N$ ) can lead to a low performance of the controller.



**Figure 4:** Temperature behavior and actuators action ( $\lambda_c=0.001$ ;  $\alpha=0.75$ ).



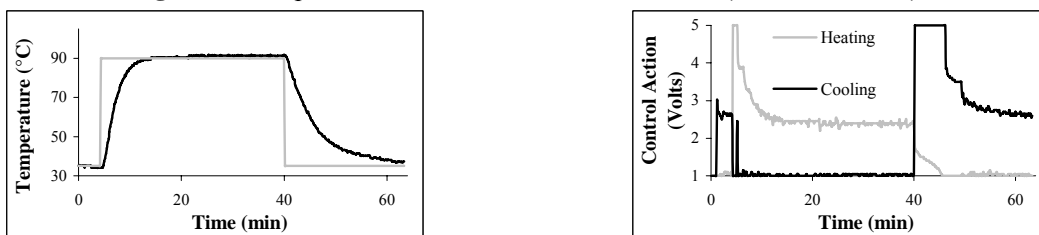
**Figure 5:** Temperature behavior and actuators action ( $\lambda_c=0.01$  ;  $\alpha=0.75$ ).



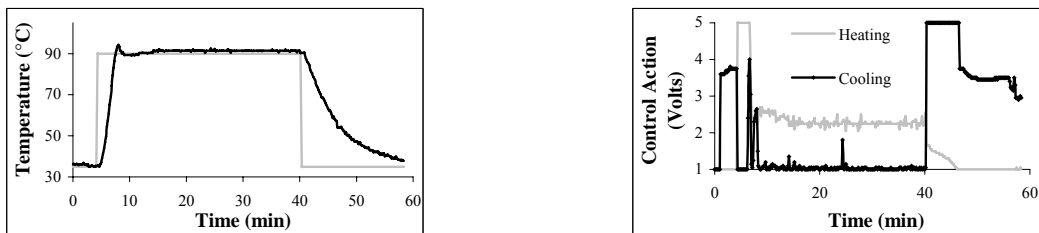
**Figure 6:** Temperature behavior and actuators action ( $\lambda_c=0.1$  ;  $\alpha=0.75$ ).



**Figure 7:** Temperature behavior and actuators action ( $\alpha=0.50$  ;  $\lambda_c=0.1$ ).



**Figure 8:** Temperature behavior and actuators action ( $\alpha=0.96$ ;  $\lambda_c=0.1$ ).



**Figure 9:** Temperature behavior and actuators action ( $\alpha=0.75$ ;  $\lambda_c=0.1$ ;  $N=12$ ).

### On-line Adjustment of Recurrent Neural Network (RNN)

Data used as patterns for FANN off-line training were obtained for the system without chemical reaction, with the reactor containing only water. FANN is applied to the controller in recurrent form (RNN), as a model of the process. The model will present flaws if used to represent the system dynamics while the polymerization reaction of styrene in suspension takes place, the differences being due to the absence of modeled disturbances and the exothermic characteristics of the chemical reaction, as well as the non-linearities of the system.

A change of dynamics will take place due to two main reasons: firstly, the  $\Delta H$  of reaction (the styrene polymerization reaction is an exothermic process) and also the heat capacity modification, because instead of only water, there are polymer/monomer particles in suspension, with significant variation of this ratio during the reaction progress. Secondly, other disturbances should be considered, such as the boiler steam pressure variation and water pressure variation used as the process cutting fluid. Classic PID controllers like the NMPC fail in temperature control during the chemical reaction due to deviations and inherent nonlinearities in the process, that comes into evidence as NMPC approaches closer the desired temperature when the adaptation from the linear layer of the FANN (output neurons) is used to solve the problem. In this study we did not develop other types of adaptation strategies, which are an interesting topic for other studies of this system.

To correct variations between the model and the system, an on-line methodology of the adjustment of the weights and bias of the output layer of the RNN was applied through GA, with a group of  $J = 10$  used patterns of the report of the process where  $(J + \max(d_1, d_2))$  points are stored for the training, where  $d_1$  and  $d_2$  are the involved delays. The range of variation of weights used was of 0.001 and the code of the GA used is the same as that of the off-line training. A population of 30 individuals was applied to the algorithm with 110 generations without harming the computational processing in the sampling interval, the criterion being the minimization of the quadratic mean error for the case of the reactor carrying out the styrene polymerization

reaction in suspension.

The use of the genetic algorithms is justified in this application because the problem is not linear (an intrinsic characteristic of the model used. FANN), GA being applicable to this type of problem.

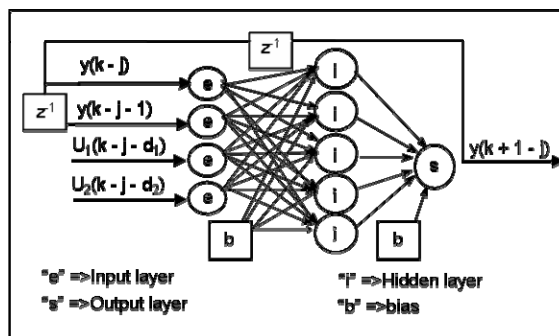
The choice of the GA parameter values must be such that it maintains the diversity of the population in each generation and does not make the computational effort (for a very large population, for example) much greater; given the limitation in the sampling time used (10 seconds), the parameters must be adjusted in a way to allow an adaptation of the model to each interval of sampling, without the system becoming unstable.

Another factor that can harm the stability of the system with adaptation is the use of values that are too large for the weight variation range to be implemented. We suggest a preliminary test to determine these values, for example using the reactor with water, in order to determine an adequate interval for the system without becoming unstable. The use of low values for the weight variation range is a recommended procedure to reduce the risk of instability of the system, which can be increased until a satisfactory result is obtained.

It is important for the stability of the system that the patterns of training used in the off-line training are representative and that the obtained model, which will be adapted, represent the identified system well. For the adaptation algorithm (GA), the objective is the correction of deviations between the model and nonlinearities of the polymerization reaction.

Taking into consideration that the network is used as a forecast model for the predictive controller, it is expected that it should have better performance if trained in a recurring way, since this is the way used in the algorithm control. Therefore, in spite of the off-line training being done in a static way, on-line weight adjustment takes place in a recurring way.

Figure 10 shows the FANN representation in recurrent form (RNN) used for on-line weights adaptation. It can be noted that the output is determined by the net and used as pattern input. The actual process output is used as the input for the network, which characterizes a recurring representation for it.  $J$ , in the figure, represents the size of the point window (number of patterns) used for training, from the history of the process.



**Figure 10:** FANN with the representation used in recurrent form (RNN).

Taking into consideration that weight adaptation is necessary due to the deviations (afore mentioned) that take place in relation to the obtained model for the off-line training, it is expected that they do not happen in an enhanced way during short time intervals. Thus, it is logical to conclude that there is no need to adapt all FANN weights, since they do not cause significant alterations in relation to two consecutive sampling intervals. Therefore, values from the off-line training can be used as the starting point for the beginning of adaptation.

From these considerations, the only adaptation done was of the weights and bias of the output layer of the FANN. In this way, the GA chromosome is built as shown in Figure 11 and the number of parameters to be optimized (number of chromosome genes) is given in Equation 3. For the purpose of this study, we employed five neurons on the hidden layer (NNI) and one in the output layer (NNS), totaling six parameters for optimization – a low number if all weights and bias were to be optimized - a total of 31 - with little computational effort.

$$N_{\text{par}} = \text{NNS}(\text{NNI} + 1) \quad (3)$$

For on-line optimization, time is a factor that must be a permanent concern, as the optimum value, or one nearest to it, for the parameters must be found in a shorter interval than the time interval used for the sampling and implementation of the control actions.

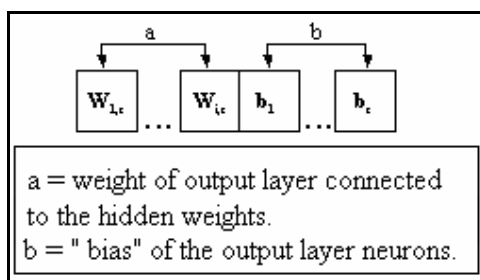
The searching space of the weights (the range of

variation of these) is determined at each new interval from parameters used in the last interval. The definition, then, of the limits that will determine the weights variation range and FANN bias is given by Equation 4.

$$\begin{cases} L_{\text{Sup},i} = \gamma_i + \delta \\ L_{\text{Inf},i} = \gamma_i - \delta \end{cases} \quad (4)$$

where  $L_{\text{Sup},i}$  and  $L_{\text{Inf},i}$  are the upper and lower limits of each parameter (weights and bias), respectively, for searching space definition of the GA optimization. The variable  $\gamma_i$  defines the values of each parameter “i” used in the previous interval. The value of  $\gamma_i$  will define the searching space size, which is equal to 0.001 for this work. This procedure allows the process to be swift because, although it does use random values for optimization these are, in a certain way, close to the optimum.

The GA code used was the same as for the off-line network training. For on-line application the algorithm coded in Object Pascal language was used, with programming in Borland Delphi language. The genetic algorithm uses the population of the 30 individuals for the case of the chemical reaction. According to the PC capacity installed at the plant for the acquisition and implementation of data for the control strategy, 110 generations can be used by the method without damage of the processing of other available time controller activities.



**Figure 11:** Chromosome of Genetic Algorithm.



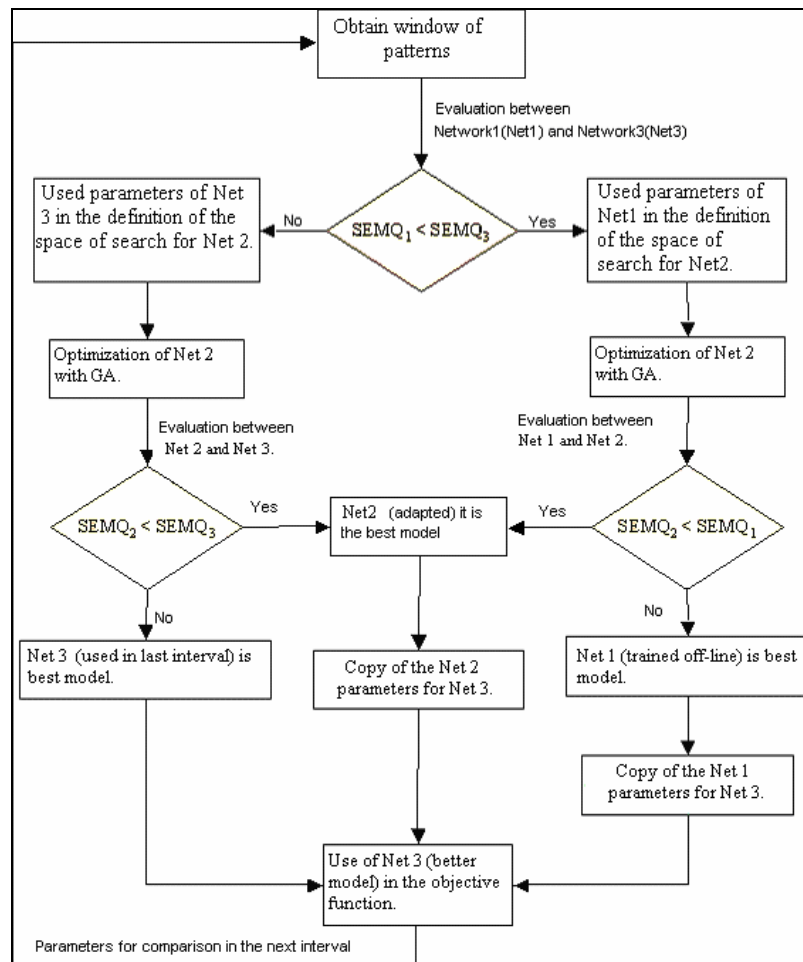
It is not always possible to ensure that the network that results from the parameter adaptation in each new interval after the 110 generations is always better than the one that was implemented in the previous minute, or the one that was trained off-line. An algorithm was therefore developed in a way to avoid, in a given moment, the use of parameters that can lead the model towards a worse performance. This could cause divergence in the solution, since the parameters are adapted from the values obtained from the previous minute, running the risk of destabilizing the control system. The algorithm was developed from the principle that under no circumstance could a model with lower adjustment than the one performed by off-line training be used. In this way, if a better model is achieved, the parameter values will be used in a future interval as the prime condition for the new adaptation. Therefore, there is a need to work with three parallel model sets, as follows:

1. Network 1(Net1): This is the model from the off-line training. It does not undergo any alteration/adaptation throughout the entire system operation.

2. Network 2(Net2): This model undergoes, at each interval, adaptation of its parameters (weights and bias of the output layer). The adaptation always derives from the best parameters among the competitive networks.

3. Network 3(Net3): This network receives, in each minute, the parameters of the best Network in the previous interval. Network 1 does not undergo adaptation; Network 2 is constantly adapted and the best network used in the previous interval, Network 3.

All analyses and considerations are based on the patterned window used for training/adaptation. The criterion for choosing the best of the three models is based on the sum of the quadratic average error (SEMQ), as shown in Equation 5, for the set of patterns considered in the window. Thus, it is considered that the model presenting the lowest sum of errors will be used in the control law as the forecast model. Figure 12 show the algorithm used for the on-line adaptation of the empirical model process, where SEMQ1, SEMQ2 and SEMQ3 are the quadratic average error sums for Network 1, Network 2 and Network 3, respectively.



**Figure 12:** Scheme of the Algorithm used for on-line adaptation.

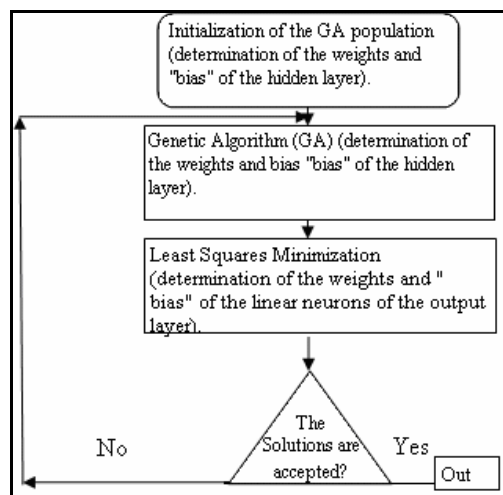


Figure 13: Simplified Scheme of the FANN training.

$$SEMQ = \sum_{i=1}^J (y_{\text{real},i} - y_{\text{pred},i})^2 \quad (5)$$

In Equation 5,  $y_{\text{real}}$  is the real output of the process,  $y_{\text{pred}}$  is the value forecasted by the model and  $J$  is the pattern window size. The optimization algorithm, as set in this way, has as the main objective the adaptation of the network parameters in a way to ensure the magnitude of the model together with the predictive controller.

### FANN Training

FANN off-line training supplied the weights and bias for the model. A value of 40000 generations and a GA cross-over rate equal to one was used, as well as a mutation rate of 0.5% (0.005); a population of 50 individuals and a weights variation range of  $[-5, +5]$  were employed, the valid group of data covering the range of 28.98°C to 111.95°C, as shown in Figure 2. A simplified scheme of the FANN training strategy applied is shown in Figure 13.

## RESULTS AND DISCUSSION

### PID Controller

A classical PID controller was chosen initially because it is a common application in diverse industrial processes. PID performance for variations of the reference with the reactor containing only water in a split-range strategy for the control valves is shown in Figure 14.

The PID performance during the polymerization reaction of the styrene in suspension was verified; the results obtained were unsatisfactory, showing an oscillatory behavior in some areas as can be seen in Figure 15. The PID controller acts satisfactory for maintaining temperature range for water, but for the chemical reaction the performance is decreased by nonlinearities and the exothermic reaction, and the classical PID controller is not capable of maintaining the desired temperature range.

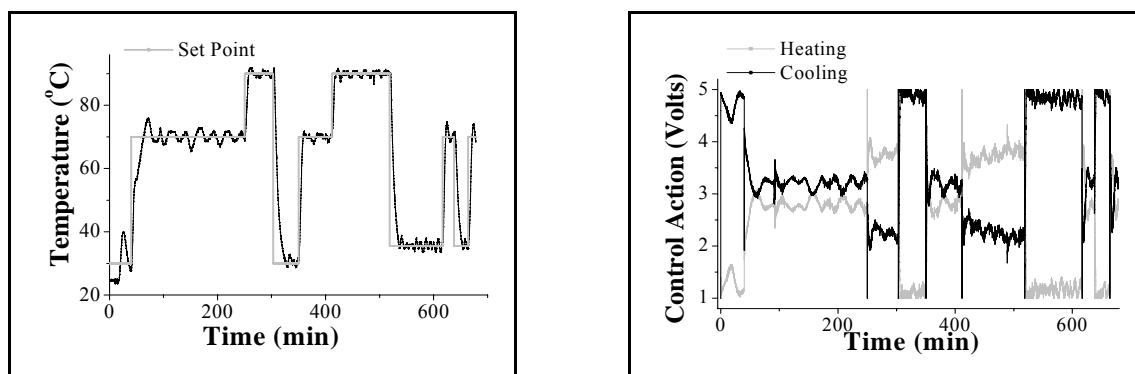


Figure 14: PID answer for reactor containing water and actuators action.

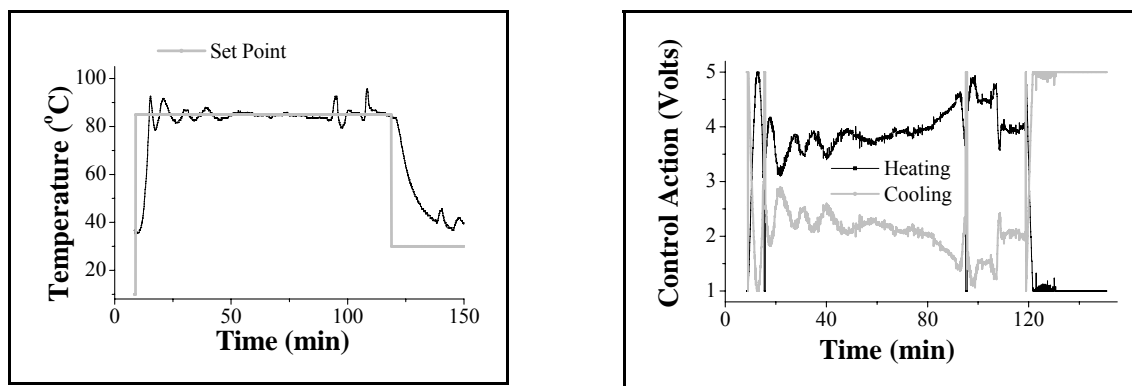


Figure 15: PID answer with chemical reaction and actuators action.

## NMPC Controller

### a) NMPC with RNN

The described NMPC was applied in a MISO control strategy (two inlets; cooling and heating and one exit; temperature). Results obtained in the instance without chemical reaction are shown in Figure 16; the results with chemical reaction are shown in Figure 17.

The RNN is a good model for the process without chemical reaction, where the system is the same in which FANN training patterns were generated, as well as for the case with chemical reaction, where the system is no longer identical to the patterns. It undergoes variations in its dynamics due to changes occurring during the reaction. However, the system presents occurrences of overshoot and offset during the reaction, the RNN being unable to represent such differences exactly, failing to presenting the desired operational conditions as classic controller PID.

### b) NMPC: RNN Adjust On-Line

As a way to correct these deviations, a methodology for on-line adjustment of weights and bias was applied in the FANN output layer, in a

recurring way to the original FANN, using Genetic Algorithms (GA), with a point window of 10 sampling intervals, 110 interactions, a population of 30 individuals and a weight variation range of 0.001. The results obtained with the adaptation for the chemical reaction of styrene in suspension are better than NMPC without adaptation, as shown in Figure 18, eliminating overshoot and, for maintenance of the reference, eliminated offset. The adaptation algorithm aims at minimization of the sum quadratic error between the value predicted by the model (FANN) and the real experimental value.

The adapted strategy using GA presented superior results in the transition of the set-point (eliminating overshoot) and for maintenance of the reference, eliminating offset. The adapted NMPC controller was efficient in dealing with the problem of nonlinearities in the studied control system, its use being practicable since the training FANN represents the simple control system (without reaction) inside the desired ranges of operation.

Finally, the adapted NMPC controller was tested during chemical reaction with high noise in the temperature signal reading, with satisfactory results even during this high disturbance in the input signal (noise in the signal of the temperature). The results are shown in Figure 19.

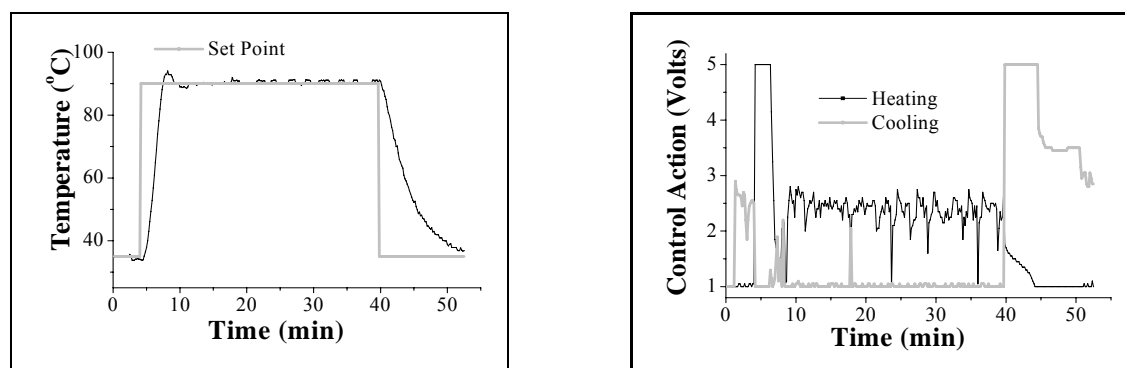


Figure 16: NMPC controller answer with reactor containing water and actuators action.

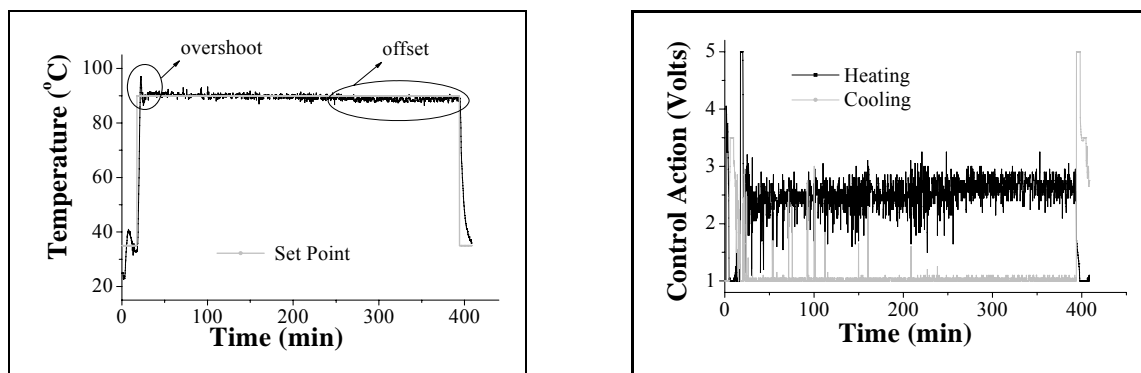


Figure 17: NMPC controller answer with chemical reaction and actuators action.

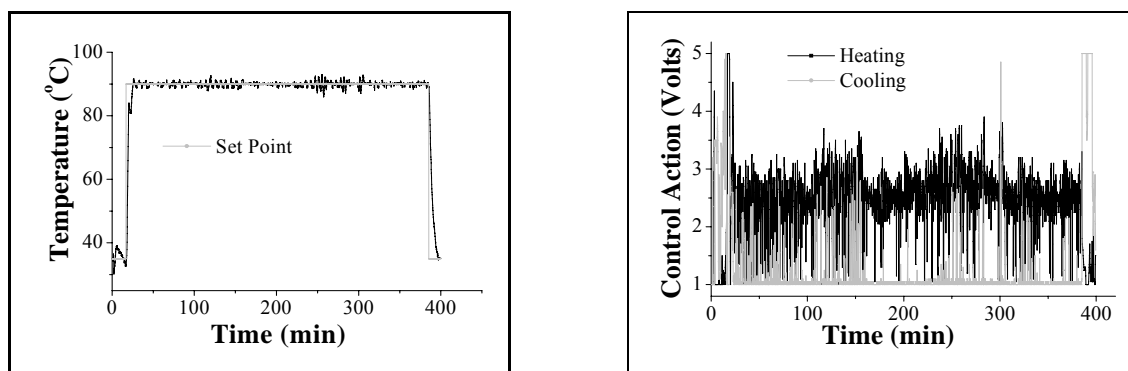


Figure 18: NMPC answer with adaptation (GA) and chemical reaction and actuators action.

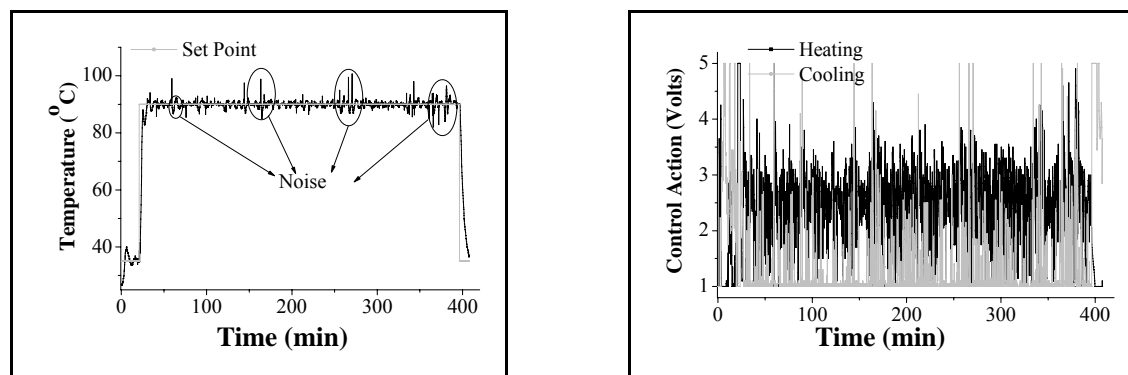


Figure 19: NMPC answer with adaptation and noise in temperature signal and actuators action.

## CONCLUSIONS

Temperature control of the polymerization reaction of styrene in suspension is important because deviations in the maintenance of the temperature can affect the final product quality.

An approach using a first order system with dead time and a classical PID controller application did not present good results for the case of the chemical

reaction, where the implicit difficulties of the process have a large influence on the controller's performance.

The complexity of the temperature control process, together with difficulties such as system modeling, dead time, variable dynamics, and noise disturbances as well as others that cannot be identified, was dealt with by exploring resources that can minimize these modeling problems.

Application of NMPC using a model based on a

FANN trained in off-line form and applied in a recurrent form (RNN) showed satisfactory results (performance superior to PID) for NMPC using the system identical to the generator training patterns of FANN. For the case of the polymerization reaction of styrene in suspension, the NMPC exhibited superior performance to PID. However, due to nonlinearities, dead time and non-modeled disturbances, there was overshoot in the transition of temperature, as well as offset in the maintenance of the temperature. The exothermic reaction occurring in the reactor and non-modeled disturbances produce an alteration in the dynamics of the system and the offset throughout the reaction, which can also be explained by alterations in the system dynamics that were not incorporated to FANN.

The adapted strategy using GA presented superior results in the transition of the set-point (eliminating overshoot) and for maintenance of the reference, eliminating offset.

The occurrence of temperature signal noise that could cause the controller to become unstable was tested. These deviations were compensated by the on-line adaptation, presenting satisfactory performance for the studied case.

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#### NOMENCLATURE

$U_1$	Heating control action.
$U_2$	Cooling control action.
NNI	Number of neurons in the intermediate layer.
SEMQ	Selection criterion for weights in the adaptation method.
$y$	Controlled variable value.
$y(k-1)$	Value of controlled variable in the previous instant.
$d_1, d_2$	Value of dead times for the heating and cooling control action, respectively.

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